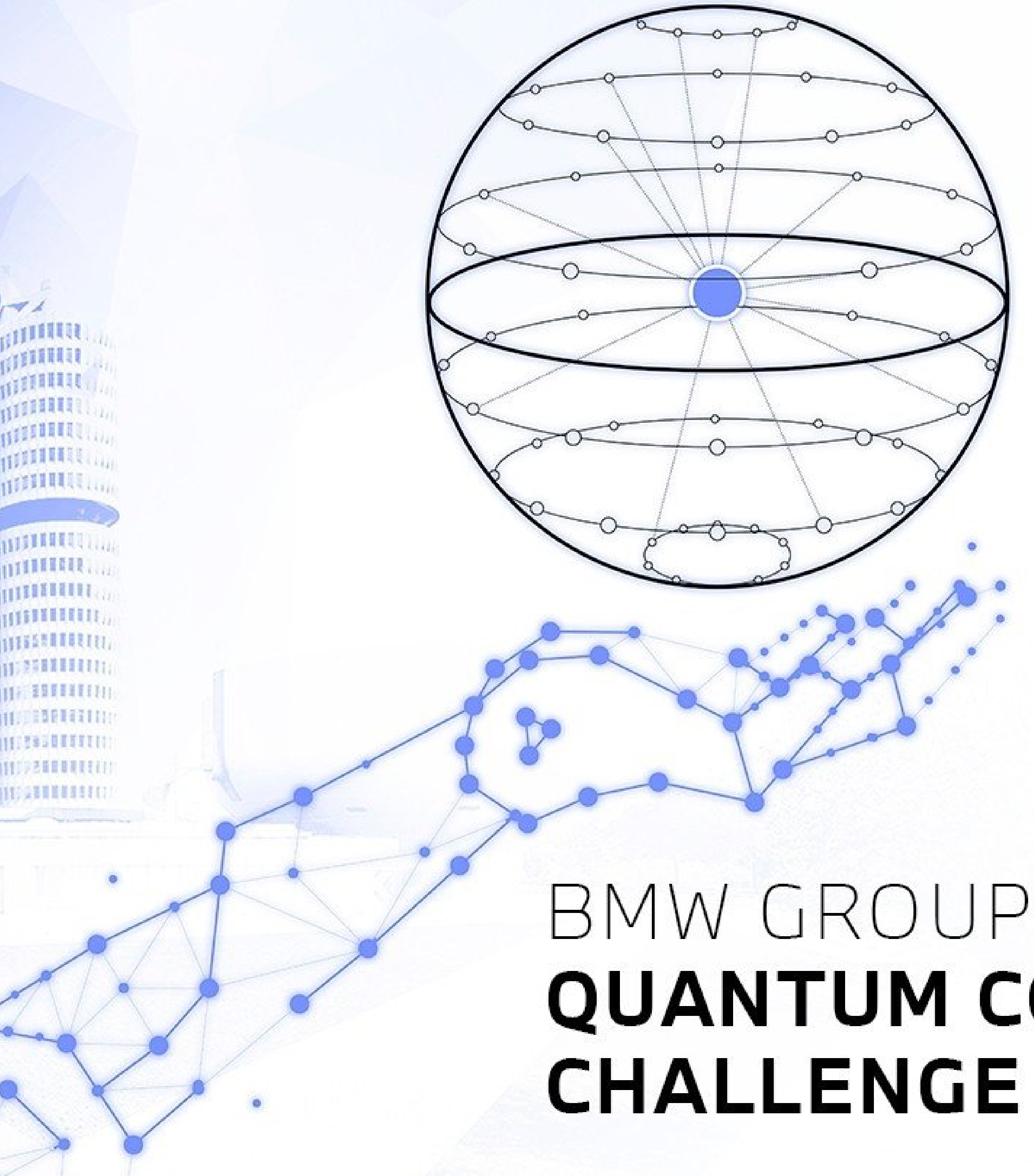
September 24, 2021 : **Round One Submission**



BMW GROUP
QUANTUM COMPUTING CHALLENGE

The Quantum Musketeers

Meghashrita Das, Amaury de Miguel,
Anuj Mehrotra, Vardaan Sahgal

Quantum Defect Analyser

Motivation

Bringing foremost quantum computing advances into real world challenges

Business Impact

Quantum Computing innovations (like in Quantum Machine Learning), are redefining the manufacturing landscape by giving advantage in discovery , product development and process optimization & automation. Early adoption will help to unlock the opportunities in those areas which are enormously difficult to challenge.

NISQ-ploration.

To explore inclusion of Quantum Computing with a search for an Industrial Application that can use NISQ ready hybrid Quantum Neural Network (QNN) programs to offload the heavy lifting processing, from classical computing (GPU/TPU) to Quantum Computing platforms which can be deployed today.]

Accelerate.

Native randomness of Quantum Computing gets inherited by approaches like **Quantum Kernel Alignment** (QKA) for **Hybrid Quantum Neural Networks** (QNN), which helps to achieve better generalization rates for machine learning models with faster convergence during training **(not mandatory, as depends on complexity of dataset & problem)**[1][2]

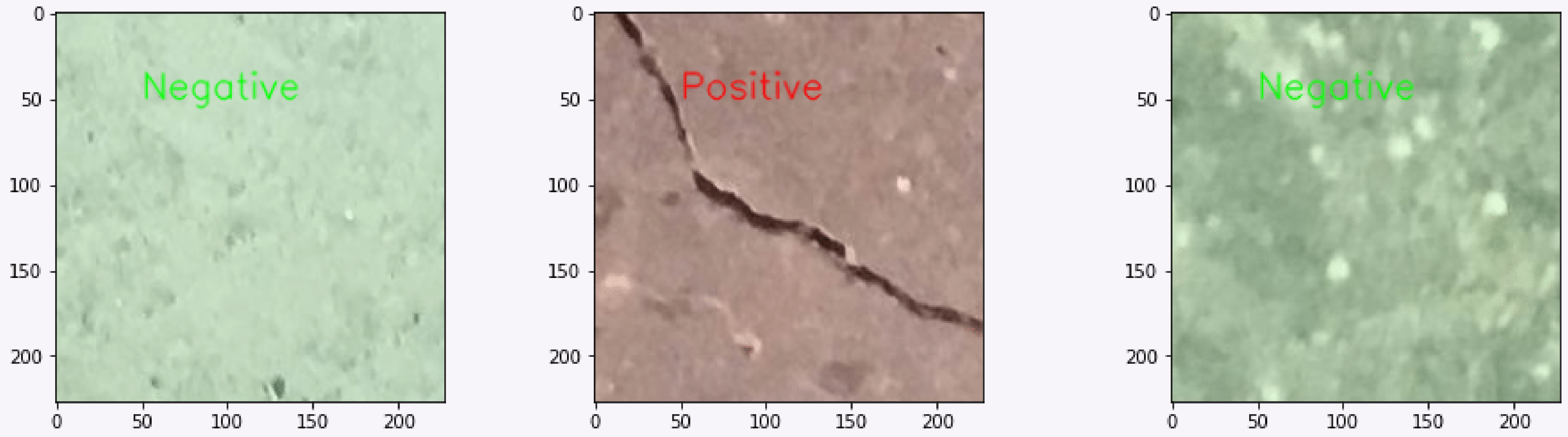
[1]Feature Kernel Alignment for Point Cloud Convolution : https://arxiv.org/pdf/2004.04462.pdf
[2]Covariant quantum kernels for data with group structure : https://arxiv.org/pdf/2105.03406.pdf

Use case: Surface crack detection

Towards an Automated Quality Assessment System

Problem Statement

Surface cracks are major defects that plague the manufacturing industry. The datasets [1] contains images of various concrete surfaces with and without crack. Each class has 20000 images with a total of 40000 images with 227 x 227 pixels with RGB channels generated from 458 high-resolution images (4032x3024 pixel)[2] .



Modern control processes in manufacturing test the limits of advanced analytics, especially when employing machine learning and analyzing multiple variables.

Rapid developments in compute software and hardware have drastically shifted quality control and inspection from manual methods to automated routines for examination, especially in an era of Industry 4.0.

Quantum computing helps to find new correlations in data, enhance pattern recognition, and advance classification beyond the capabilities of classical computing, thus adding a digital control to Industry 4.0 technologies.

[1]Özgenel, Çağlar Fırat (2019), "Concrete Crack Images for Classification", Mendeley Data, v2 http://dx.doi.org/10.17632/5y9wdsg2zt.2
[2] Generation method proposed by Zhang et al (2016)

Innovation

Exploring Quantum Image Processing

01

High performance CNN models lead to large numerical workloads and require expensive GPU/TPU for deployment. We explored the use of quantum machine learning which is a research area that explores an interplay of ideas from quantum computing and classical algorithms. Hybrid quantum layers and kernels can be suitable for complex Industrial Application datasets, which is why we chose it to explore it on our surface crack detection classification application.

Use of QKA routine

We explores the use of an iterative quantum-classical algorithm: Quantum Kernel Alignment (QKA), where quantum hardware is used to execute parameterized quantum circuits for evaluating the quantum kernel matrices, while a classical optimizer tunes the parameters of those circuits to maximize the alignment. Iterative algorithms of this type can be further speeded up by reducing latency between the quantum and classical calculations.

02

Platform Agnostic

03

In an attempt to mitigate the latency between quantum and classical calculations, due to Qiskit framework compatibility, integration is possible with **IonQ Quantum Computing** platform hosted in **AWS Braket** ecosystem, **Honeywell** Quantum Computing platform on Microsoft Azure, as well as solutions like Qiskit Runtime with its QKA routine . Qiskit Runtime is a new architecture offered by **IBM** Quantum that streamlines computations requiring many iterations with reduced latency of operations having a tighter and closer integration to the quantum backend.

Model categories explored:

Classical CNN

QKA + "Hybrid" NN

"Hybrid" Quantum NN

Applicability

Considerations and Constraints

constraints

Practicality

If the quantum distribution prepared by the device is far from the one assumed, most of the burden would lie on the classical post-processing. It is not clear how much of the method's efficiency is given by the quality of the samples from the quantum devices and how much is achieved by the post-processing steps.

Scalablity

Million - hundred thousands are the range of qubits that are needed to handle extremely large datasets where state-of-the-art classical ML starts to struggle. The scale factor of qubits required for loading the dataset and representing samples has a polynomial scaling with the resolution and number of input samples

Data variety

Datasets commonly found in industrial applications have a large number of variables that are not binary. Representation of classical variables can quickly consume valuable qubits if a pure quantum solution is being sought out.

considerations

Problem set

Problems that are currently hard and intractable for the classical ML, for example, generative models in unsupervised and semi-supervised learning can serve to be a viable selection to explore

Data patterns

Datasets with potentially intrinsic quantum-like correlations may provide the most compact and efficient model representation, with the potential of a significant quantum advantage even in the NISQ era with 50-100 qubit systems.

Hybrid ideas

Hybrid algorithms where a quantum routine is executed in the intractable step of the classical ML algorithmic pipeline can be explored for usage today

Quantum Defect Analyser

amazon web services

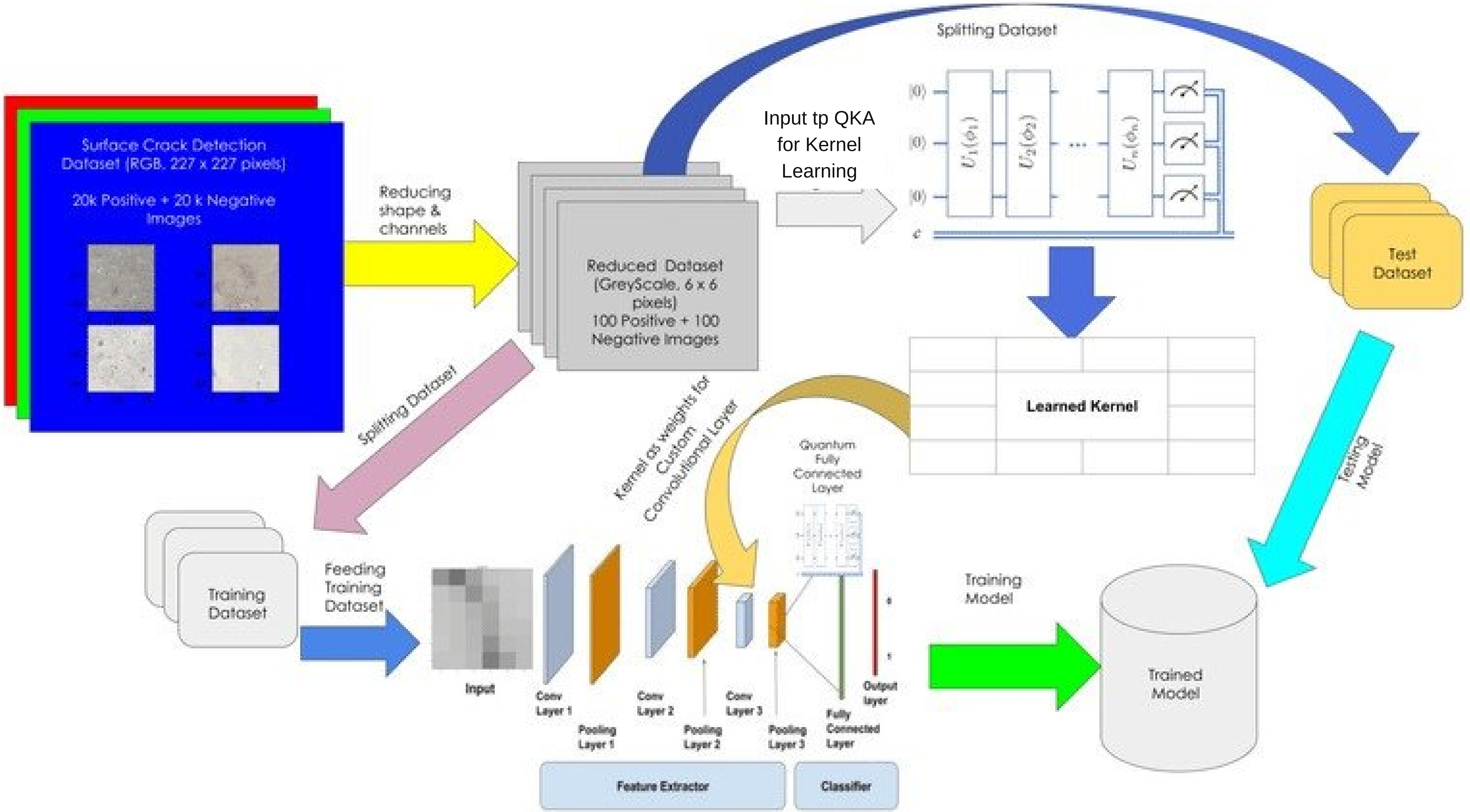
BMW GROUP

Rolls-Royce Motor Cars Limited

Applicablity Timeline:

Source: https://www.forbes.com/sites/moorinsights/2021/03/23/ionq-takes-quantum-computing-public-with-a-2-billion-deal/?sh=4d27d37d5d06

QKA for QNN Architecture



Role of QKA for Image Classification

Machine Learning Approaches Comparison

Aspects	1 CNN with Pretrained ResNet50	2 QNN without Pretrained Model	3 QKA For QNN without Pretrained Model
Training Epochs Required for Convergence to minimum loss	14	5	4 : **Three Fold Faster than CNN**
Model Generalization	**Max Training Accuracy** : 85% **Max Validation Accuracy** : 95%	**Max Training Accuracy** : 85% **Max Validation Accuracy** : 95%	**Max Training Accuracy** : 88% **Max Validation Accuracy** : 94%
Sample Size	227x227 pixel 1000 images , with 3 Channels	227x227 pixel 1000 images , with 3 Channels	[1] 8 x8 pixel 1000 images , with 3 Channels
Number of Layers	ResNet50 native Layers + 5 additional Layers	5 CNN+ 1 Hybrid layer	3 CNN+1 Custom Convolution layer with weights from QKA + 1 Hybrid layer

Due to QKA, understanding of underlying group structure of data helped to increase accuracy

[1] Used very small dimension in order to reduce the overall resource utilization & training time for the simulation

Role of QKA for QNN :

Tested Model Results 1

Model 1: Classical CNN

A pretrained Resnet50 with last 5 NN layers modified. Image input resolution = 227x227. 1000 Positive + 1000 Negative Images , Channels = 3.

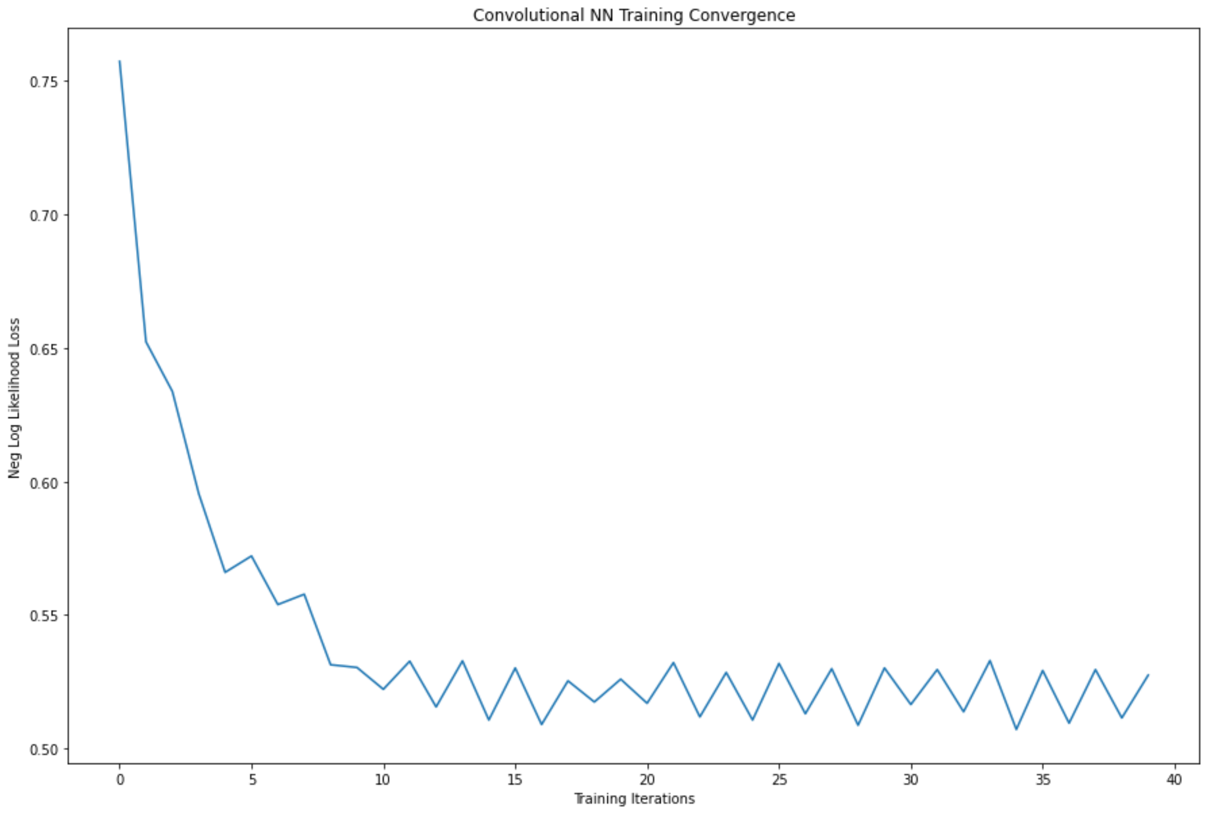


Fig.1 CNN Training Convergence

Fig.2 CNN Training vs Validation accuracy

Train Accuracy= 85%

Val Accuracy= 95%

Role of QKA for QNN :

Tested Model Results 2

Model 2: Hybrid QNN

5 NN layers with one Hybrid Quantum Circuit layer . Image input resolution = 227x227. 1000 Positive + 1000 Negative Images , Channels = 3.

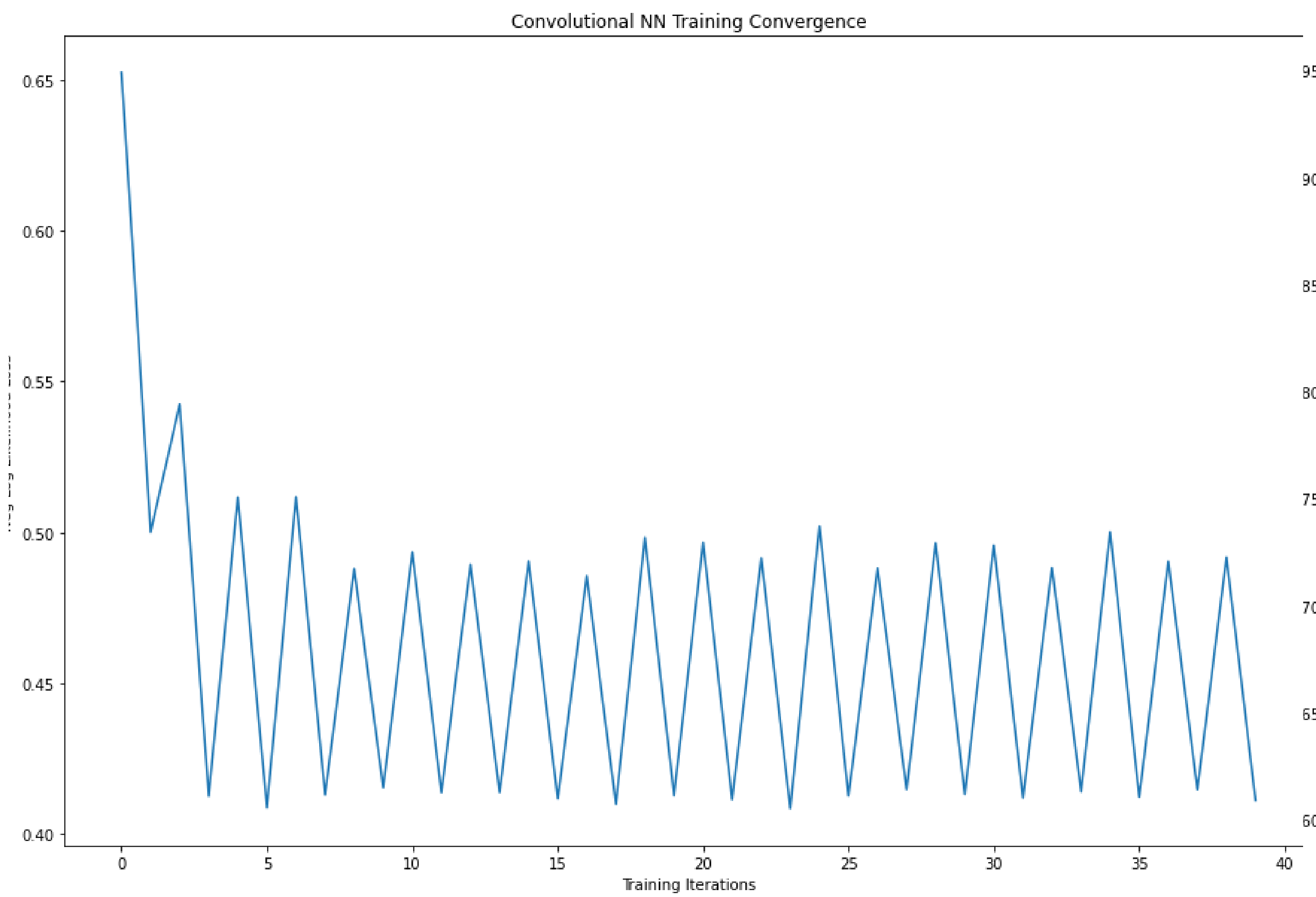


Fig.1 Hybrid QNN Training Convergence

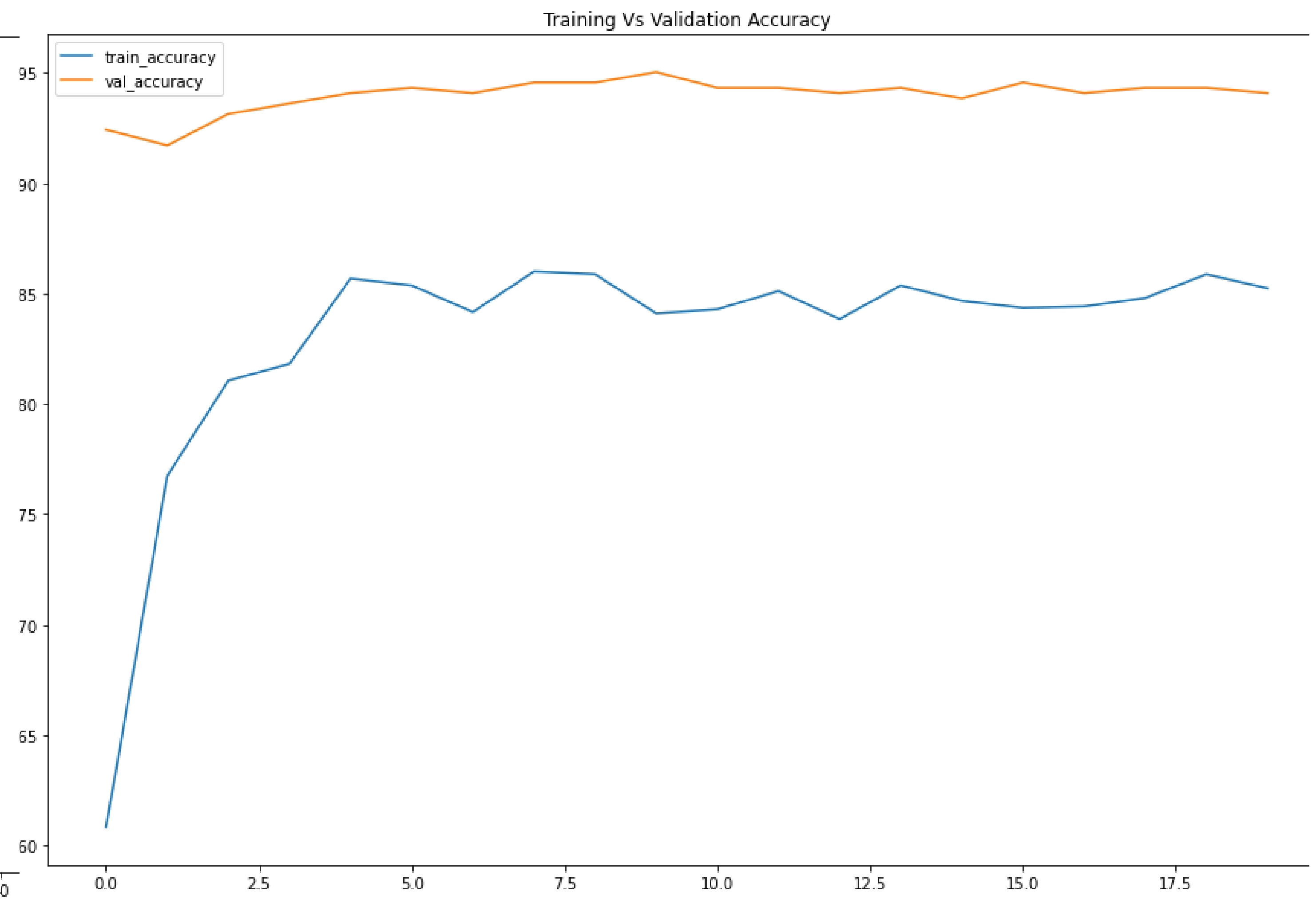


Fig.2 Hybrid QNN Training vs Validation accuracy

Train Accuracy= 85%

Val Accuracy= 95%

Quantum Defect Analyser

Model 3: Hybrid QNN +QKA Layer

Role of QKA for QNN :

Tested Model Results 3

3 NN layers , one custom convolutional layer with weights from Quantum Kernel, one Hybrid Quantum Circuit layer . Image input resolution = 8x8. 1000 Positive + 1000 Negative Images , Channels = 3.

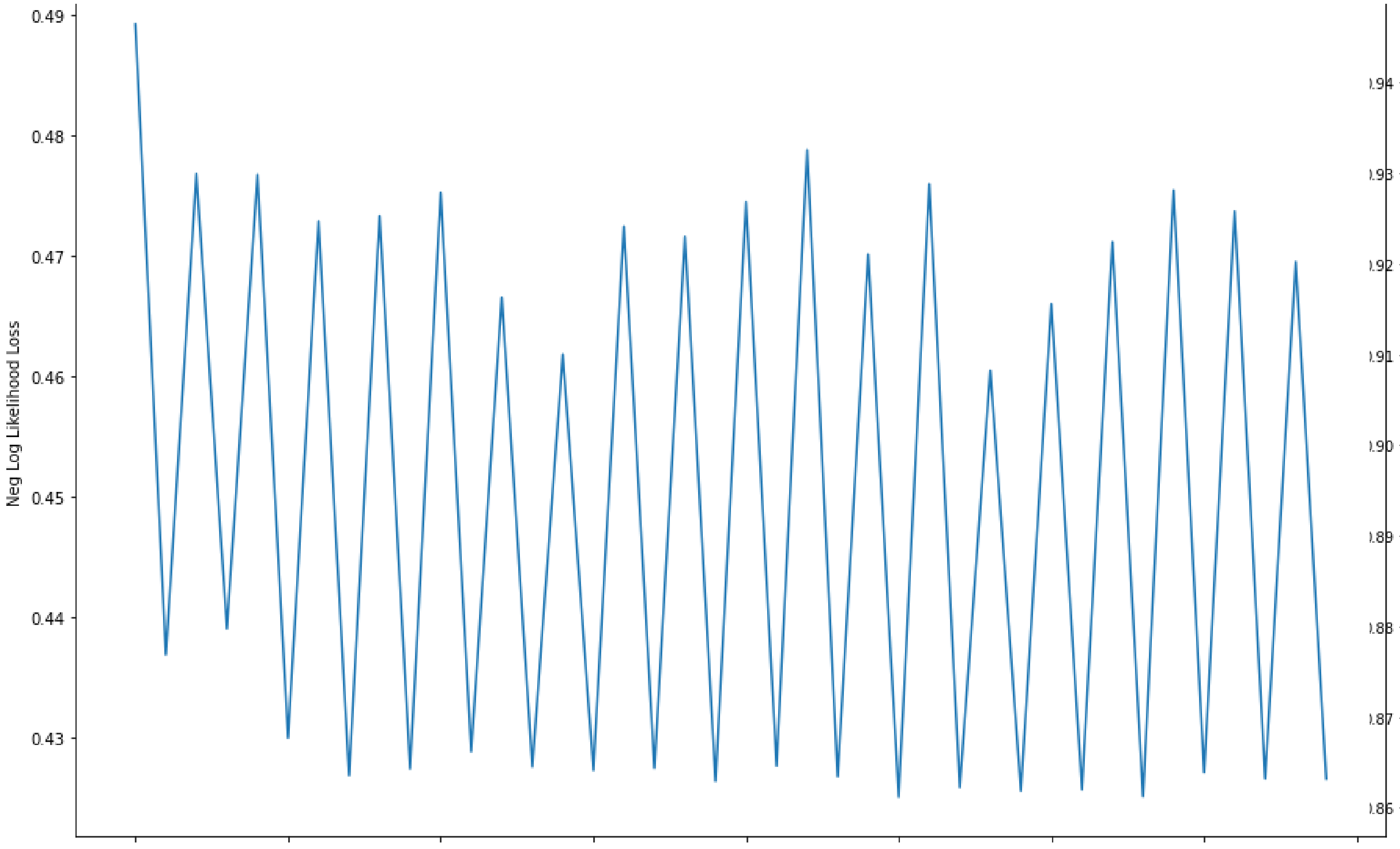


Fig.1 Hybrid QNN Training Convergence

Fig.2 Hybrid QNN Training vs Validation accuracy

Train Accuracy= 88%

Val Accuracy= 94 %

amazon web services

BMW GROUP

MINI

Rolls-Royce Motor Cars Limited

Technology Stack

Libraries and softwares used for the project

- **Python v3.8**
- **Pytorch v1.9**
- **Qiskit v0.29**
- **Nvidia Cuda v11.2**
- **IBM Quantum**
  - Qiskit QML Application Module
  - ibmq_qasm_simulator v 0.1.547
- **Jupyter Lab**

python™

PyTorch

Qiskit

NVIDIA CUDA

IBM Quantum

jupyterlab

Quantum Defect Analyser

amazon web services

BMW GROUP

Rolls-Royce Motor Cars Limited

Future Plan for Round 2

Exploring other Data Loading Programs

As Industrial Application dataset considered to be complex large datasets, so plans are to explore and implement approaches like Quantum Generative adversarial networks and Pytorch libraries like TorchIO

Reduce the latency

Due to the advanced emerging tools like the Qiskit Runtime latency between Quantum & Classical compute platforms can be reduced for these Industrial applications which wants to resolve classification problems, can be explored to be made much more realizable by a much larger technical attendance and are not particularly limited to the research community.

Enhanced Realization of Quantum Advantage by Usage of Quantum Kernels

A quantum kernel on a dataset with an exploitable pattern may be explored to realise a speedup for the NISQ era and ready deployment with a potential polynomial speedup over classical kernels[1]

[1] https://research.ibm.com/blog/quantum-kernels

BMW GROUP

Rolls-Royce Motor Cars Limited

amazon web services

Thank you

September 24, 2021 | BMW Quantum Computing Challenge 2021